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Pediatric In-Patient Days Predictive Model

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PEDIATRIC IN-PATIENT DAYS PREDICTIVE MODEL

BY

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A doctoral project submitted to the faculty of the Medical University of South Carolina in partial fulfillment of the requirements for the degree Doctor of Health Administration in the College of Health Professions

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Abstract of Doctoral Project Presented to the
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Degree of Doctor of Health Administration

Chairperson: Kit Simpson, DrPH, Professor, Medical University of South Carolina

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Scott Goodspeed, DHA, Program Director, Executive Master of Healthcare Leadership, Brown University

The study objective is to develop a predictive model for pediatric inpatient days based on ambulatory outpatient visits and emergency department visits. This model aims to study the relationship between ambulatory visits and inpatient days, and determine if in-patient days can be predicted based on sub-specialty practice. Such a model does not currently exist, and when created and validated such a model could be utilized for various important management decisions, including refined insight into inpatient capacity and operational efficiency for self-governing children's hospitals with large sub-specialty practices.

The data set was a sample of convenience from one health system in the PEDSnet database. The requested data set yielded 3,832,428 distinct records, inclusive of all billed encounters for January through December 2017.

Multi-regression analysis was used to predict variations in weekly occupied days over time. Ordinary least squared regression model results were used to examine the predictive power of outpatient variables. This enabled comparison of beta values for as many combinations of predictors as possible, in an efficient manner and yielded 80 models.

The conclusion was that big data from one children's hospital within a children's health system was able to predict in-patient occupancy for greater than 50% of the variance.

Keywords: predictive modeling pediatric census, ambulatory practice impact on inpatient census in pediatrics, pediatric outpatient models that drive weekly ADC

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Chapter 1 - Introduction

Background and Needs

The national healthcare system is inundated with uncertainty and volatility, as Congress and President Trump have not been able to successfully agree upon how to best address the future of the 2010 Patient Protection and Affordable Care Act. Concurrently, the industry continues to move forward with the aim of transitioning to value based care focused on improving quality of care while actively and effectively decreasing the cost of care.

While this work is an intense and demanding focus of healthcare leaders today it is interesting to note that these are not new concerns to the healthcare industry. Forty-five years ago, Wennberg & Gittelsohn (1973) wrote of concerns about the immediate effects on institutions and pondered the effects on community services caused by healthcare legislative changes. In the 1970s, legislation was implemented aimed at controlling the price of services and insurance with Phase 3 of the Wage and Stabilization Act of 1970 and the implementation of the state insurance commission (Wennberg & Gittelsohn, 1973).

Over the last 45 years healthcare leaders have been facing pressure to reduce the cost of health care and ensure coverage and services, this remains a national priority today. Wennberg and Gittelsohn (1973) suggested the answers to concerns about community services may "depend on statistics that describe on a per capita basis, the input of resources, and the production of services, and the effect of these on health status" (p. 1102). In 2013, Theorist Clay Christianson has suggested specialty hospitals can leverage economy-of-scale and offer focused expertise.

Various models of Christianson's concept are in existence, ranging from the long-standing Hospital for Special Surgery model established in 1863 (HSS, n.d.) to Cancer Treatment

Centers of America founded in 1988 (CTCA, n.d.). Another example is Select Medical, founded in 1996. One of the nation's largest operators of specialty hospitals and outpatient rehabilitation clinics, Select Medical is recognized as one the Best Managed Companies in America by Forbes magazine (Selectmedical, 2017). Select Medical continues to have an aggressive growth strategy developing multiple partnerships with large hospital systems to provide specialized services (Barkholz, 2017). Self governed children's hospitals also fall into this type of model by providing highly specialized expertise and advocacy for acutely and chronically ill children, as well as the most medically complex children.

Children's hospitals serve a unique role in the fabric of the national health care delivery system, and are atypical because they cover much larger geographies than traditional hospitals. There are approximately 250 children's hospitals in the U.S., which means that 1 in every 20 hospitals is a children's hospital (CHA, n.d.). Notably 14% of admissions to children's hospitals come from other acute care hospitals (CHA, n.d.) (Appendix A). Of the 250 children's hospitals, fewer than 50 are a self-governed children's hospital. Self-governed children's hospitals are independently governed and solely focused on the care of children and/or high-risk delivery mothers; they are not part of a larger adult health system. Self-governing children's hospitals provide communities with significant community benefits that average $104 million a year (CHA, n.d.).

The breadth of the role children's hospitals play in the care of children across the nation is outlined by Children's Hospital Association (CHA) and includes the following highlights. CHA 2015 annual report showed the average children's hospital sees 7,993 inpatient visits, 41,913 emergency room visits, and 179,908 outpatient visits, and 83% are trauma centers (CHA, n.d.) (Appendix B). Children's Hospital Association 2012 annual survey on utilization and financial indicators showed 40% of children depend on Medicaid, 6% of children on Medicaid are medically complex, and 40% of Medicaid funding goes to care for those 6% of children (CHA, n.d.) (Appendix C). Payer sources vary between the type of visit and care provided: inpatient visits are 54% Medicaid and 39% private insurance; emergency room visits are 63% Medicaid and 29% private insurance; and outpatient visits are 43% Medicaid and 42% private insurance, with the reminder of coverage by other sources (CHA, n.d.) (Appendix D). Additionally, children's hospitals train virtually all pediatric residents and pediatric sub-specialists, and 35.3% of NIH's support for pediatrics occurred at children's hospitals or related Pediatric Departments (CHA, n.d.).

The specific and unique role children's hospitals serve in children's health was recognized when Congress approved and implemented a new reimbursement program called the Children's Health Insurance Plan (CHIP), in 1997, which today covers over 9 million children (Strauss, 2017). In the midst of the current political turbulence, CHIP was allowed to expire on September 30, 2017, in spite of enjoying bipartisan support historically and presently. Congress assured children's hospital leaders that CHIP would be renewed, yet it was intertwined with tax reform and further healthcare negotiations. The program was renewed in February 2018.

Specialty hospitals are intended to meet the needs of specific patient populations from areas of relatively large geographic areas. Given such large service areas; it is essential that all the specialty hospitals are capable of accommodating all requested admissions; denying or turning away patients can lead to unmet needs for children's care, impair referral relationships and potentially lead to bad publicity. Forecasting or maintaining excess capacity can be detrimental to economic viability. It is an arduous task to achieve and maintain an appropriate balance between supply and demand. The current process to assess capacity needs is complex and is impacted by significant external and internal factors specific to hospital throughput factors; the process is generally a qualitative approach based on experience, judgment and gut instinct (Proudlove, Black, & Flecther, 2007).

As noted above children's hospitals generally have large subspecialty practices associated with the hospital that serve as one of the primary drivers of admissions. Goodman (2009) reviewed pediatric studies of variation in pediatric care and noted that differences in the quality of ambulatory care are thought to be an important cause of admissions, however, this line of thinking lacks empirical data. The symbiotic relationships between these physician practices and children's hospitals are clearly recognized, however, the association between physician practice characteristics and demand for care at children's hospitals has not been systematically examined.

Study Objective/Research Question

The study objective is to develop a predictive model for pediatric inpatient days based on ambulatory outpatient visits, including telehealth, urgent care, primary care, specialty clinics, and emergency department visits. The aim of this model is to study the relationship between ambulatory visits and inpatient days, then determine if in-patient days can be predicted based on sub-specialty practice. Such a model does not currently exist and when created and validated such a model could be utilized for budgeting, workforce development, capital planning, master facility planning and various other important management decisions. This type of predictive model could offer refined insight to inpatient capacity and operational efficiency for self-governing children's hospitals with large sub-specialty practices.

The remainder of this paper will be arranged as following: Chapter two provides a brief overview of existing and related literature about predictive modeling that may inform the design and application of this research. Chapter three outlines the methodology used to develop the predictive model, data set, variables and statistical analysis. Chapter four will report findings and limitations of the study. Chapter five closes with conclusions and a summary.

Chapter 2 - Review of Literature

Although there are various predictive models in the literature specific to various topics, few if any studies have examined the intent of this research project. Minimal information was found in the literature on models that are able to predict in-patient census or estimate bed demand for specialty hospitals; moreover there is limited research evaluating pediatric hospitalization risk factors, particularly in infants and toddlers (Mikaeloff, Moride, Khoshnood, Weill & Breart, 2007). Capan, Hoover, Jackson, Paul and Locke (2016) used a single neonatal intensive care unit (NICU) to develop a census forecasting model, based on time series models compared to the more traditional fixed average census methodology. The outcome of this work suggested the model could offer valuable insight to various management decisions yielding better staffing decisions (Capan, Hoover, Jackson, Paul & Locke, 2016). Yet that approach does not address the interconnection between specialty clinic practices and in-patient census projections, which is the aim of the current study.

Because relatively few children's hospitals exist in the U.S. it is not surprising that they serve large regional and geographic areas. Geographic span is not the only operational and business differentiator for children's hospitals; other considerations are the evolving marketplace dynamics such as the impact of market consolidations, narrow payer networks, adult-oriented accountable care organizations, and alternative adult-oriented payment methodologies that are not easily applicable to children's healthcare. Franca and McManus (2017) reviewed data from 2004 – 2014 to test the hypothesis that the availability of pediatric definitive care is more restrictive than adult care and is decreasing disproportionately. The study included 66 acute hospitals in the Commonwealth of Massachusetts, the researchers concluded pediatric hospital care is becoming increasingly consolidated, and many more common conditions are not being treated in the community (Franca & McManus, 2017). Franca and McManus (2017) further observed that, over the decade of their study, pediatric admissions fell 11.3% and the percentage of patients admitted to academic medical centers was twice that of adults. To the authors knowledge, theirs was the first attempt to study a state's pediatric hospital system. Their results suggest that regionalization likely plays a role in physician practice patterns. Other states such as Florida have more competition for the children's hospital market than Massachusetts. Multiple large adult health care systems continue to have strong and large pediatric services, or they are partnering with the children's hospitals to enable a pediatric presence.

Pediatric health care also has some clinically oriented predictive models. Over the last several decades, the PRISM score has become a well-established and recognized predictive model for pediatric critical care, and it has been used for mortality risk assessment, cost containment, and outcome quality assurance (Shann, Pearson, Slater & Wilkinson, 1997). In an effort to address shortcomings from the complexity of the PRISM model, a more streamlined model called the Paediatric Index of Mortality (PIM) was developed (Shann, Pearson, Slater & Wilkinson, 1997). Both PRISM and PIM are models that predict death, which is clearly not the focus of this study. Pediatric care is founded on the grounding principles of developmental care that spans childhood, which is yet another differentiator from adult care. Notably, the Shann, Pearson, Slater & Wilkinson (1997) model sought consistency by incorporating the PRISM age categories: less than 1 month old, 1-5 months of age, 6-11 months, 12-23 months, 24-59 months, 60-119 months and 120-191 months. Those tools stop at 16 years of age.

Mikaeloff, Moride, Khoshnood, Weill and Breart (2007) developed a predictive model, for infant and toddler ages that identified the following major variables associated with outcome: long-term disability, younger age, and ≥ 1 hospitalization before inclusion age of the study. The authors further noted in addition to medical risk factors, access to care should also be considered, and it may differ among patients based on the coverage model of care in various countries (Mikaeloff, Moride, Khoshnood, Weill & Breart, 2007). In contrast to this specific and focused approach to predicting hospitalizations, Lemke, Weiner, and Clark (2012) sought to develop a broad, population-based approach for patients of all ages who experience acute care inpatient hospitalization using claims data available to health plans in the US, intended to broaden applicability of the model. This model sought to inform decisions by payors to decrease hospitalization days, extended stays and ICU days (Lemke, Weiner, & Clark, 2012). This work showed improved accuracy of prediction based on a clinically rational model of morbidity and disease burden combined with outpatient utilization (Lemke, Weiner, & Clark, 2012). Additionally, the authors found the more risk factors associated with a patient, the higher probability of admission (Lemke, Weiner, & Clark, 2012). The framework of that study aligned with the concepts behind this proposed study aimed to understand the impact of out-patient utilization on the ability to predict pediatric in-patient utilization.

DeLurgio et al., (2009) developed a predictive model for 23 primary and specialty care clinics at Mayo Clinic in Rochester, MN. They studied 12-week intervals of outpatient visits using three approaches: univariate, multivariate based on stepwise regression, and simple averages of both models to create the third combined model; the study found the combined method to be the most effective forecast model (DeLurgio et al., 2009). The following influences were identified: trends in diseases (such as emerging disease prevalence, new treatments), seasonal influences, and casual influences change in demand, change in physician availability or marketing mix (DeLurgio et al., 2009). The fourth category was cyclical or irregular influences (such as epidemics and natural disasters), which were similarly outlined in other studies as an uncontrollable influence on admissions (DeLurgio et al., 2009; Proudlove, Black & Fletcher, 2007).

Several studies considered the impact of ambulatory care-sensitive conditions (ACSCs) on hospital admissions. ACSCs are considered to be conditions that are influenced by access to or utilization of primary care services, which may reduce admission rates and hospitalizations (Ansari, Haider, Ansari, deGooyer, & Sindall, 2012; Parker & Schoendorf, 2000). Ansari et al. (2012) used hospital admissions data of adult and pediatric patients to study two indexes: Index of Socio-Economic Disadvantage and Accessibility/Remoteness Index in Australia. Parker and Schoendorf (2000) focused on children's ambulatory care-sensitive conditions (ACSCs) when they studied whether ambulatory care could reduce the need for hospital admission. Garg, Probst, Sease and Samuels (2003) used state data from South Carolina's Hospital Inpatient Encounter Database to study potentially preventable pediatric admissions with ACSCs.

Various study designs were found in the literature. Black et al. (1991) used retrospective chart reviews. Pottick, Hansell, Gutterman, and White (1995) described the distribution of inpatient and outpatient care and studied factors associated with child and adolescent treatment for serious mental illness. Laditka, Laditka and Probst (2005) designed a study of ordinary least squares regression to estimate ACSCs and physician supply. Garg, Probst, Sease, and Samuels (2003) analyzed South Carolina ACSC pediatric admissions as a percentage of all hospitalizations when compared to other patients and county rates for ACSC. Ash, Zhao, Ellis & Schlein (2001) employed a sophisticated comparison study design of the top 0.5% group of people most likely to receive expensive care in 1998. Gittelsohn and Powe (1995) conducted a descriptive analysis to study hospital use among small areas in Maryland and identified the following key factors that may influence hospital use: demography, morbidity, medical resources, access, selection of care, and physician practice patterns. Although children's hospitals do not serve small areas, there are potential similarities with this study that should be considered as the current model is developed. Wennberg and Gittelsohn (1973) recognized that hospital beds in an area may be a rough indicator of need, but this cannot be a complete assessment unless patients hospitalized from outside the area also are considered. This is particularly true of children's hospitals that serve such large geographic and often national populations.

The literature review found hospital administrative databases were used to predict hospital admissions through emergency department triage (Sun, Heng, Tay & Seow, 2011). Parker and Schoendorf (2000) used data from the National Hospital Discharge Surveys (NHDS) and national census data to estimate national hospitalization rates. Other national data were used to study inpatient and outpatient treatment of children and adolescents with serious mental illness (Pottick, Hansell, Gutterman, & White, 1995). These studies offered insight into various data sources and evidence used in other predictive models.

Proudlove, Black, and Fletcher (2007) identified an important factor when England's National Health System (NHS) underwent a modernization effort to improve system efficiency in 1997. Their original efforts were focused on understanding the number of beds as the measure of capacity; later the importance of understanding and impacting patient flow and bed management became the focus of this work (Proudlove, Black, & Fletcher, 2007). In an extensive literature review the authors found that system improvements in both England and the United States were based on operations management theory and very little was driven by data-analytic or model testing approaches (Proudlove, Black, & Fletcher, 2007). They further determined that little is understood about how to impact patient flow effectively (Proudlove, Black, & Fletcher, 2007). The authors go on to note that extensive time and resource investments were made in process improvements and real system experimentation, largely lead by Plan-Do-Study-Act methodologies, though minimal improvement was based on other methodologies (Proudlove, Black, & Fletcher, 2007).

The complexity of the US healthcare system and its impact on patient flow and efficiency cannot be overlooked in assessing capacity. Determining capacity requires an understanding of the balance between supply and demand. The current study is designed to assess the ability of out-patient utilization to predict demand; despite the reality that the two variables can be delinked in practice. Brandenburg, Gabow, Steele, Toussaint, and Tyson (2015) identified three common themes necessary to address demand within the complexity of healthcare organizations: a systems-thinking approach, a disciplined approach to system redesign (LEAN or six-sigma where noted as common ones), and respect for people. The ability to schedule effective clinic visits directly impacts the number of patients who may need to be seen in the hospital, as well as the hospital's ability to effectively move patients through the inpatient experience; are all interrelated components.

Healthcare budgeting generally is not tightly linked between in-patient and outpatient settings, in particular clinics. However, self-governed children's hospitals usually provide both outpatient services and inpatient care, and perhaps there is a more direct relationship when considering inpatient volume. In their survey study, Bagust, Place, Ryan, Beale, and Lowson (2001) identified a range of methods that have been used to predict in-patient census; those results affirmed the lack of data driving budget predictions. The authors showed a 5-stage model for improvement in inpatient flows and suggest that most hospitals were at levels one and two (Proudlove, Black, & Fletcher, 2007) (Appendix E). Such studies validate the need for more data driven models that proactively predict census as this study aims to do in determining whether a correlation exists between outpatient visits and in-patient admissions. The development and validation of such a model could greatly improve the ability to project in-patient capacity and budget impact for specialty hospitals.

Given the novel nature of this investigation, it was necessary to broaden the literature search beyond the specific focus of the current study to help identify more remotely related studies about various predictive models. The literature was searched and found to be rich with predictive model studies specific to nurse staffing; multiple aspects of emergency room care and operational parameters; pediatric, adult and elderly care guidelines; efforts to reduce care and cost; risk-adjustment models; and coding specific to readmissions.

Studies were found about nurse staffing predictive models associated with outcomes, acuity, mortality, and cost (Needleman et al., 2011; DeGaspari, 2012, Nelson et al., 2007; Capan, Hoover, Jackson, Paul & Locke, 2016). There are also a significant number of studies looking at multiple aspects of emergency rooms utilization, optimization, and outcomes that incorporate predictive modeling. Moreover, various studies have focused on predictive models in the arena of clinical care with clear guidelines, such as readmission rates (Kansagara et al., 2011). Kasagara et al., (2011) conducted a systematic review of risk prediction models for hospital readmissions and found 7843 titles and abstracts in their initial search.

Data Analysis on Predictive Models

Various statistical and analytical designs were employed in the studies reviewed. Laditka, Laditka, and Probst (2005) used ordinary least squares regression to empirically test the relationship between physician supply, the independent variable, and ACSC hospitalizations; and the study found physician supply was positively associated with the overall function of primary health care.

Sun, Heng, Tay, and Seow (2011) used chi-square tests to study association, and logistic regression was used to predict admissions from the emergency department triage data. Various studies included demographics, ED visits or hospital admissions in the prior 3-months, method of arrival, ED acuity, and coexisting conditions (Sun, Heng, Tay, & Seow, 2011). Receiver operating characteristic (ROC) curves and goodness-of-fit were applied to the validation data set to evaluate the study model (Sun, Heng, Tay, & Seow, 2011).

Black et al (1991) studied predicting hospitalization for ambulatory patients with pneumonia. The multivariate analysis identified five differentiating variables (serious comorbid illness, preexisting lung disease, multi-lobe involvement on x-ray, likely aspiration, and symptoms of less than 7 days or more than 28 days) that predicted high-risk verses low risk patients for admission.

Ansari, Haider, Ansari, de Gooyer and Sindall (2012) used univariate and multiple logistic regressions, reporting odds ratios and 95% confidence intervals for predictors of ACSC admissions compared to non-ACSC admissions.

Eggli, Desquins, Seker, & Halfon (2014) conducted an observational study of 2 million anonymous insured individuals in the 26 cantons in Switzerland to analyze the impact of extensive risk adjustment on regional comparisons and to explore the relationship between area based factors and properly adjusted rates. Binomial negative regression model was developed with increasingly detailed health status, and hospitalizations for ACSC were detected from 19 primary diagnoses (Eggli, Desquins, Seker, & Halfon, 2014). Standardized ratios with and without other detailed data, besides age and gender, measured the impact (Eggli, Desquins, Seker, & Halfon, 2014). Predictive performance was increased with morbidity inferred from diagnosis and drugs (Eggli, Desquins, Seker, & Halfon, 2014).

White, Ellis and Simpson (2014) studied hospital admissions among the homeless population in California for ACSC as they frequently lack access or utilization of preventative care. The authors used bivariate analyses and logistic regression to investigate ACSC and non-ACSC admissions of homeless patients in California. The predictive model found increased incidence of ACSC admissions based on race, age, number of chronic conditions, and a number of prior ED admissions or transfers from another healthcare facility (White, Ellis & Simpson, 2014). However, the authors of this study noted their findings are not consistent with other studies.

Mikaeloff, Moride, Khoshnood, Weill, and Breart (2007) conducted a prospective cohort study of children less than 2 years old from a French database. The study aim was to develop a predictive model of infant and toddler morbidity status based on administrative claims data (Mikaeloff et al, 2007). Multivariate logistic regression model was used to understand the impact of age and variables related to health and medications, with a 50% random sample of the study population and the other 50% were used as a validation sample (Mikaeloff et al, 2007).

Capon, Hoover, Jackson, Paul and Locke (2016) discussed the extensive use of time series analysis in healthcare forecasting, using a framework of 5-years of census data as a time series, and one year for validation. Best fitting Autoregressive Integrated Moving Average (ARIMA) models and linear regression models were used in 7-day prediction timeframes and compared using error statistic and models were compared with and without patient characteristic considerations (Capon et al, 2016). The aim of the study was to develop a forecast model for neonatal intensive care census (Capon et al, 2016).

Given the limited literature available on this topic, this current study is exploratory research. As innovative topics lack foundational work to build upon, this can also be a limitation and a challenge of exploratory research.

Chapter 3 - Methodology

Study Design

When relatively little is known about a topic or it is an unstudied topic, exploratory research is conducted to shed new light and to discover casual relationships between variables (Shi, 2008). Exploratory research is not intended to test hypotheses, but rather to hint at answers and insight to the area of study and test the feasibility of new methodologies (Shi, 2008).

The study will be a performance improvement project and should not require Institutional Review Board approval. To affirm this, a Request for Research Determination application was submitted to Nemours Institutional Review Board (IRB) and it was determined on January 31, 2018 that this study is not Human Subject Research.

Population and Sample

This study will use data from PEDSnet Network, which was launched in 2014 as part of the Patient-Centered Outcomes Research Institute (PCORI) (PEDSnet, n.d.). PCORnet is a national patient-centered clinical research network aimed to interconnect research infrastructures to enable large scale studies to be conducted faster, cheaper and better (PEDSnet, n.d.). PEDSnet is a multi-specialty database composed of electronic medical records since 2009 and is updated quarterly with information from the eight founding institutions including: Nemours Children's Health System, The Children's Hospital of Philadelphia, Nationwide Children's Hospital, Boston Children's Hospital, Cincinnati Children's Hospital Medical Center, St. Louis Children's Hospital, Children's Hospital Colorado, and Seattle Children's Hospital (Nemours Biomedical Research, 2016). Nemours data will be used for this study.

Nemours Children's Health System is comprised of two children's hospitals, one located in Wilmington, Delaware and one in Orlando, Florida. The entire enterprise provides care at over 80 sites. Services include telehealth, urgent care, primary care, specialty clinic visits, and emergency department visits. As of November 2017, PEDSnet contains 1.49 million patients, greater than 35 million visits, 11,434 unique diagnoses, more than 34 million outpatient/ED visits and greater than 1.1 million inpatient admissions from Nemours Children's Health System; that patient data establishes the basis for this study (Nemours Biomedical Research, 2016). This study will be a sample of convenience using data from Nemours Children's Health System records from the calendar year of January to December 2017. This 12-month timeframe will allow for seasonal variation to be considered that was referenced as an important consideration (DeLurgio et al., 2009).

Definition of Variables

Prior studies noted variables employed to predict admission from the emergency room were largely demographic data, and of particular note was the insurance demographic. (Sun, Hen, Tay & Seow, 2011; Parker & Schoendorf, 2000).

Independent variables for this study were extracted from the PEDSnet Nemours Children's Health System data and are broken down into three primary demographic categories: Patient; Provider; and Site. Within the patient demographic category the variables originally in the initial data included: de-identification number, which is a specific de-identified number per individual participant and is a categorical variable. Patient gestational age is a continuous variable and will be measured as the median age/month/clinic. Ethnic is a categorical variable representing patients with a Hispanic indicator and will be calculated by percent per month per clinic. Black, White, Hispanic and Other are categorical variables, each measured by the percent of each categorical patients seen by month in the clinic. Male is a categorical variable measured as male equals 1 and female equals 0. Male and female are calculated as percent per month per clinic. Age categories are continuous variables and were grouped as: 0-1 years, 1-7 years, 8-13 years, and 14 years plus. Medicaid, private pay, and other payor sources are categorical variables that will be calculated as percent per month per clinic (Appendix F).

The provider demographic category includes de-identified providers identification number and the provider specialty. Both of these variables are categorical.

The site demographics category includes the variables specific to the care site identification number and includes the following types of ambulatory care visits: telehealth visits (telehlth), urgent care visit (UC), primary care (PC), specialty care visit (SpecCare), emergency department (ED). These variables are categorical and will each be calculated as percent per month per clinic. The total number of visits is a continuous variable that will be measured per month per clinic.

Figure 1 outlines the independent variable categories and shares provider demographic variables.

Figure 1 – Independent Variable Categories

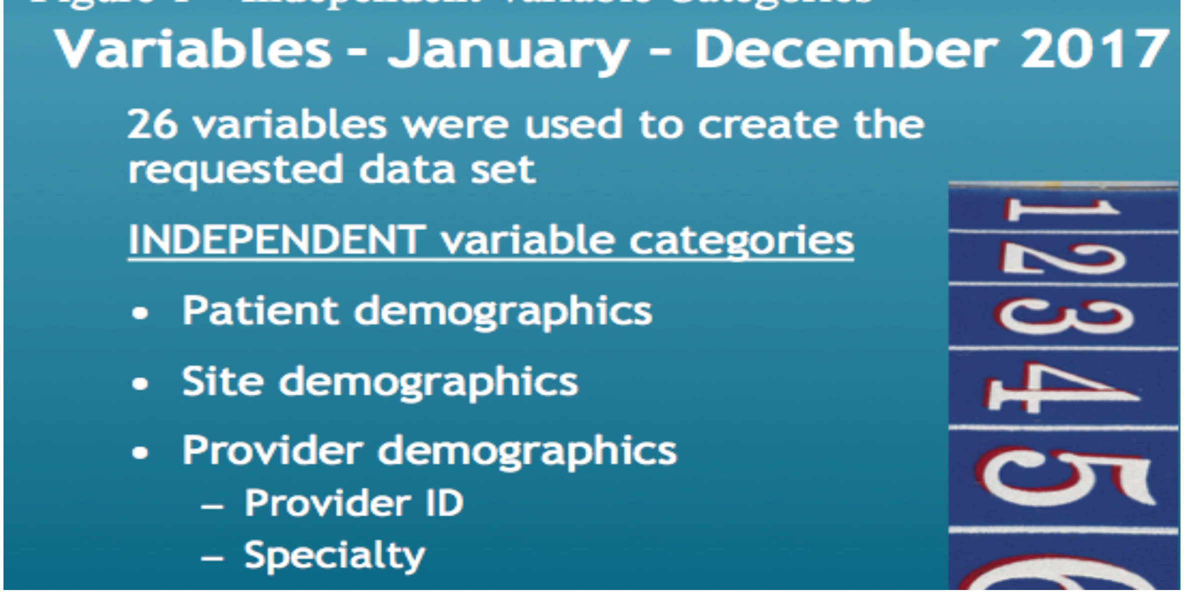


Figure 2 outlines the variable data set details by patient and site demographic category.

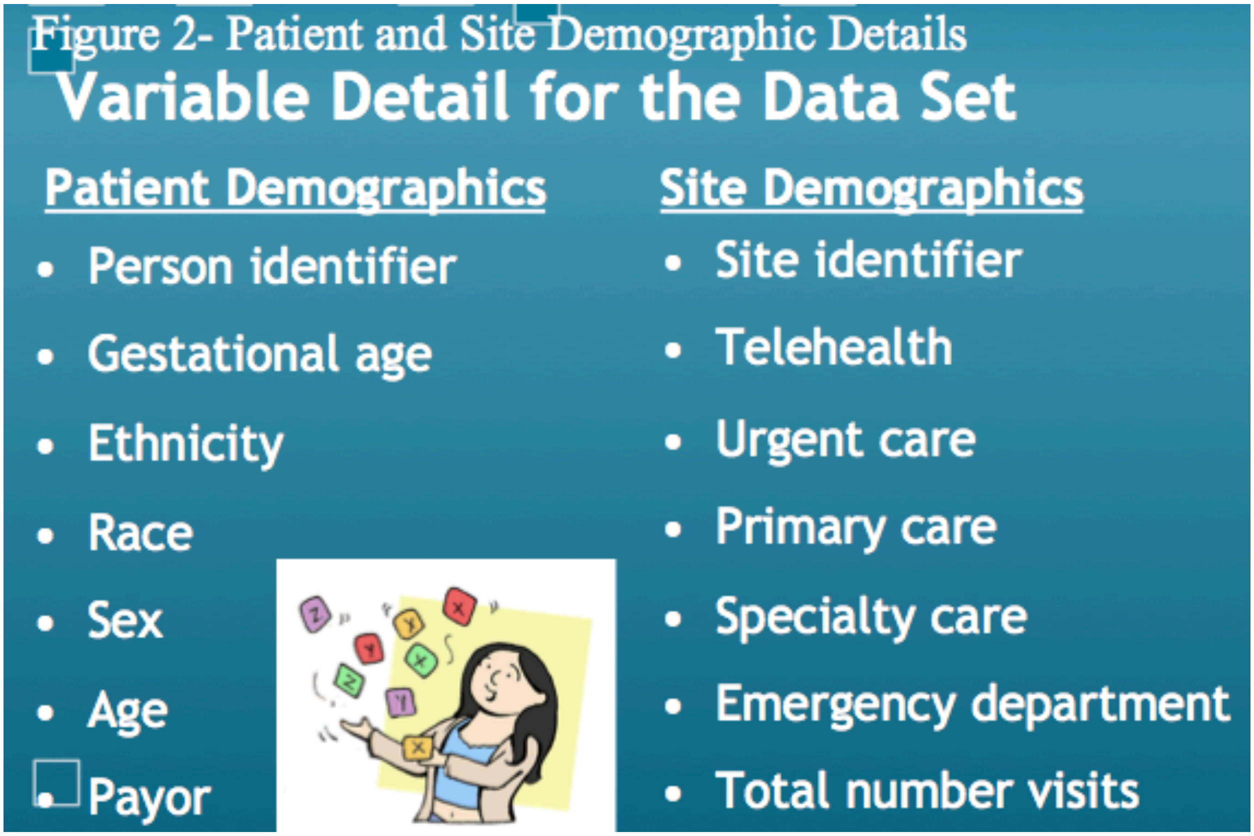


Figure 2- Patient and Site Demographic Details

The dependent variable of this study is average daily census by week. This is a continuous variable that was report by the Nemours Children's Hospital finance department.

Figure 3 summarizes the independent and dependent variables for this study.

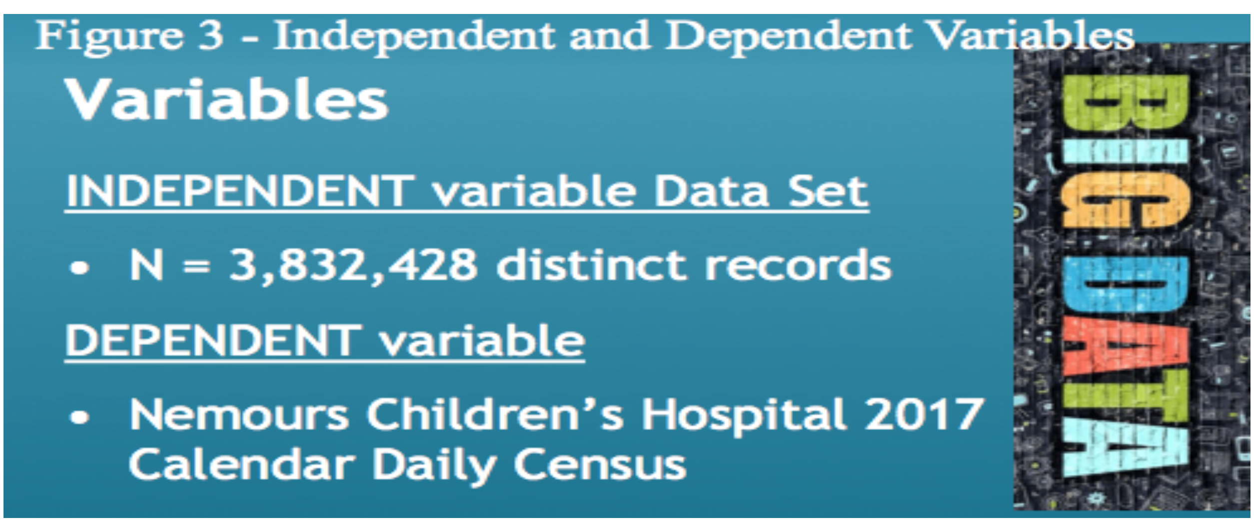


Figure 3 - Independent and Dependent Variables

Data Collection

Nemours Institutional Review Board 1 confirmed the PedsNet data request for this project was not human subjects research. The data requested from PedsNET yielded a total n = 3,832,428 distinct records. The data set was inclusive of all billed encounters for January through December 2017 for children cared for at Nemours Children's Health System.

Data Analysis

The aim of this current study is to develop a multi-variable predictive model to predict in-patient days. The dependent variable was number of inpatient days per week for one hospital based on data from one calendar year of admissions. The predictors were weekly aggregates of outpatient visits that took place one or two weeks prior to the week of the relevant admissions. This limited the data set to 50 observations. Ordinary least squares regression models were used to examine the predictive power of the outpatient variables. This approach was selected to maximize the predictive power and to enable us to compare beta values for as many combinations of predictors as possible in an efficient manner. The exploratory analysis included automatic backwards and forwards selection approaches (using Proc Stepwise, and Proc Max R) as well as manually fitted models informed by management logic, and pre-specified hypotheses. Forty models for each of the two different approaches were evaluated and considered from the perspective of "insights gained" by the first author and two researchers trained in health administration.

Figure 4 outlines the data analysis methodology used.

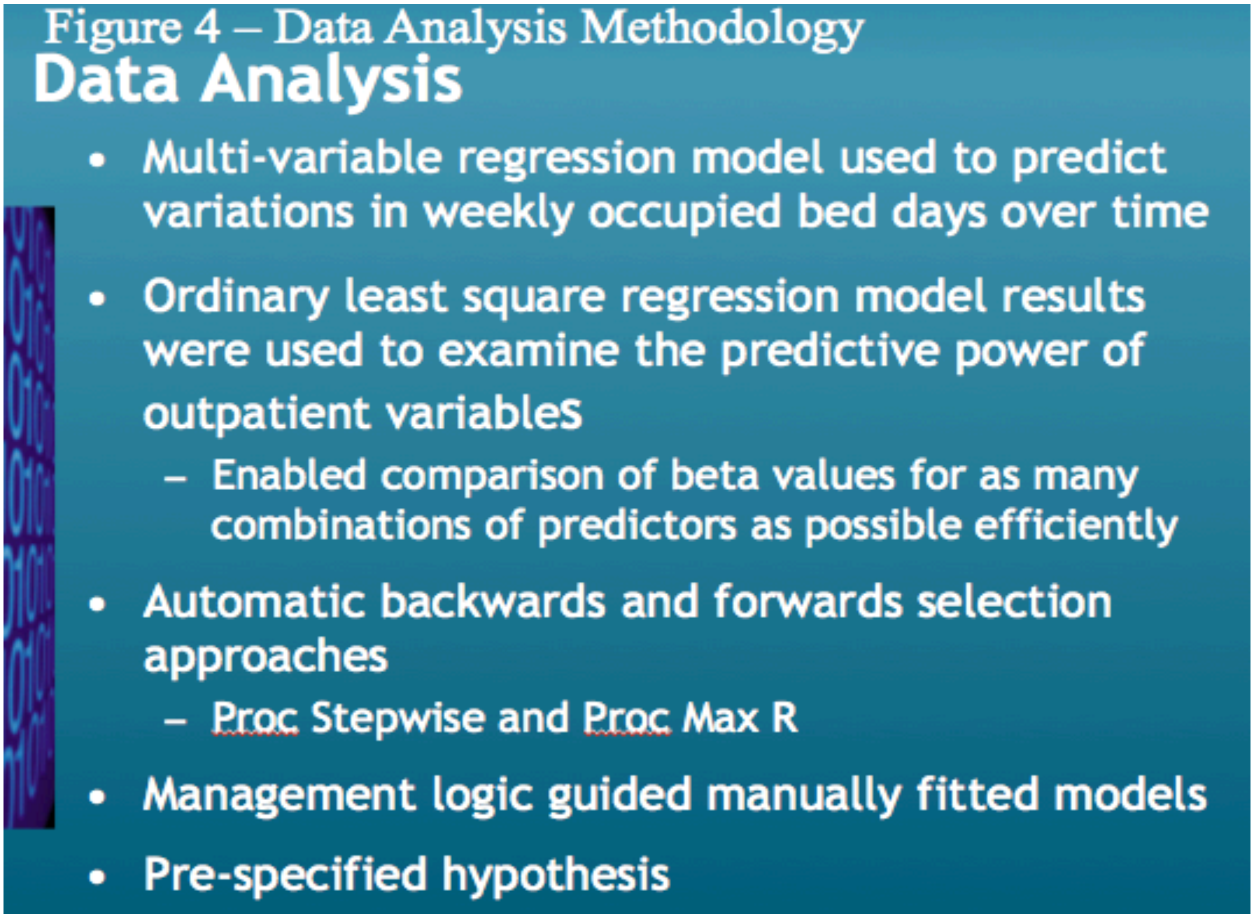


Figure 4 – Data Analysis Methodology

Multiple iterations of the all observations data set were grouped and modeled with this big data to identify the best variables to study. Visits were grouped into each independent variable category, and visits were totaled by practice specialty and total number of visits per week. These groupings were then used to predict the best variable predictors of in-patient occupancy in the following week 1 and week 2 after the out-patient visit. The computer then selected 37 variables that accounted for variation and those models were further refined down to 10 variables. No perfect model was identified.

Figure 5 defines the data set construction methodology.

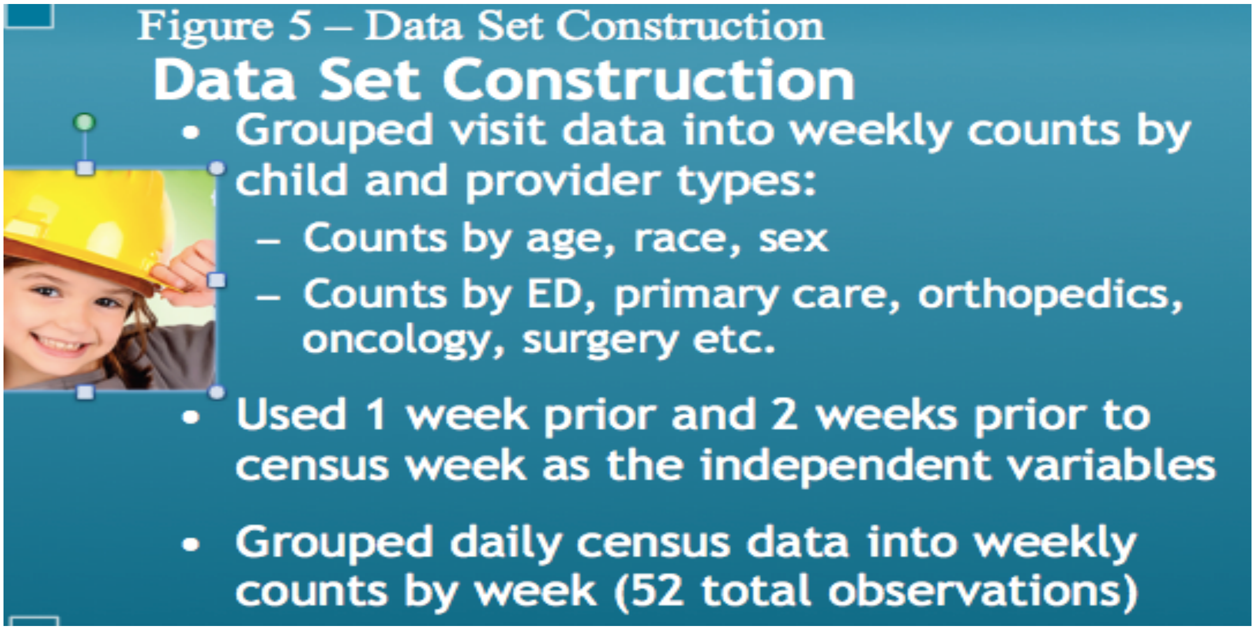
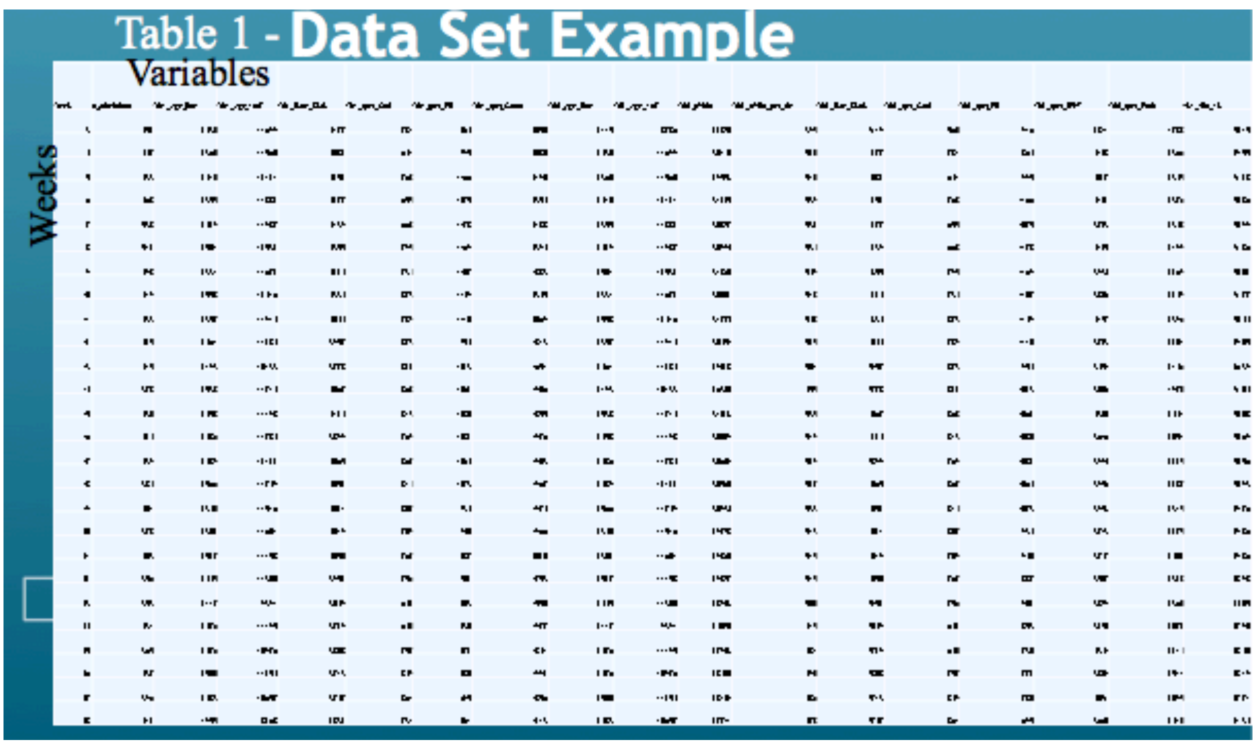
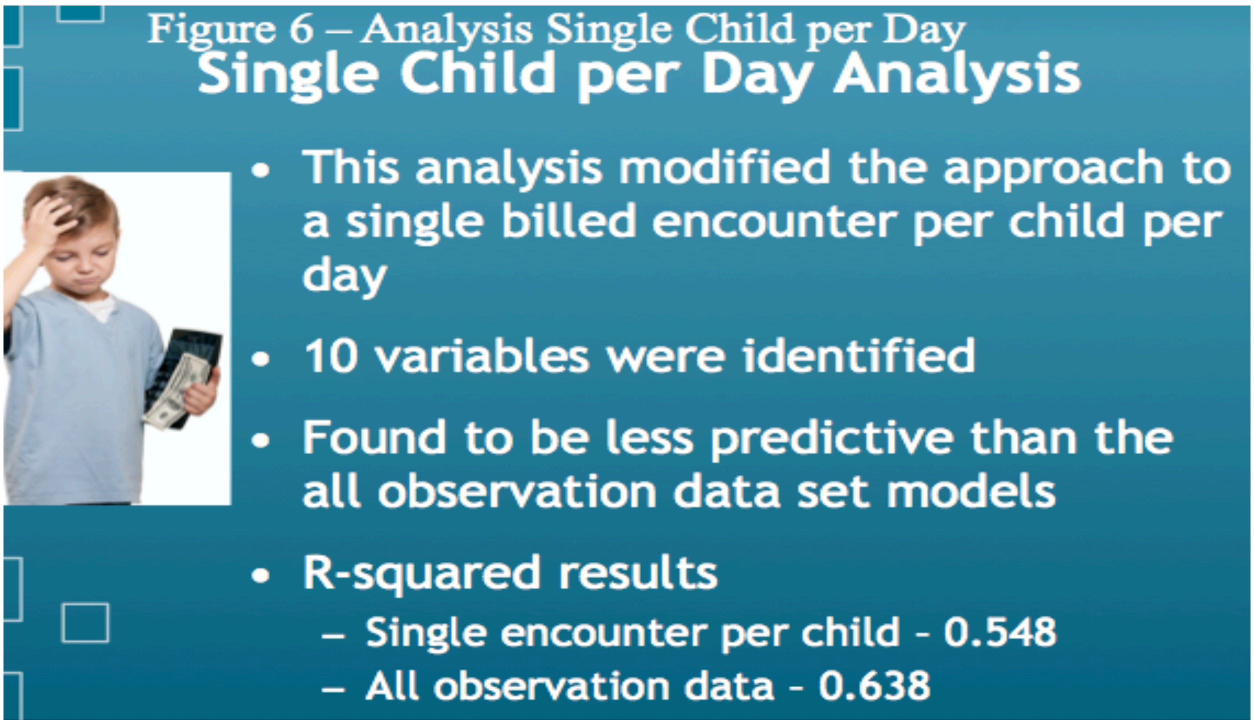


Table 1 offers an example of how the data set was constructed.



Next the data was analyzed based on a single child per day approach, which limited the billed encounters to a single one per child per day. These models were less predictive than the all observations data set models developed. The one child per day models found 10 predictors that accounted for 0.548 r-squared. The all observations analysis found 10 predictors that accounted for 0.638 r-squared, resulting in 10% improvement when all observations were included.

Figure 6 summarizes the Single Child per Day Analysis.



Forty models were developed from the all observation data set and were studied for practical application. The forty models were built based on week 1 and week 2 predictors for admission. Week 1 visit predictors included: Hispanic, ED visits, ENT, Gastroenterology, Mental Health, Neurology, Orthopedics, Primary Care, Surgery, Urology, and Other Specialties. Week 2 visit predictors included: Hispanic, ED visits, Gastroenterology, Neurology, Orthopedics, Primary Care, Urology, and Other Specialties.

Figure 7 outlines the variables in the All Observation Data Set.

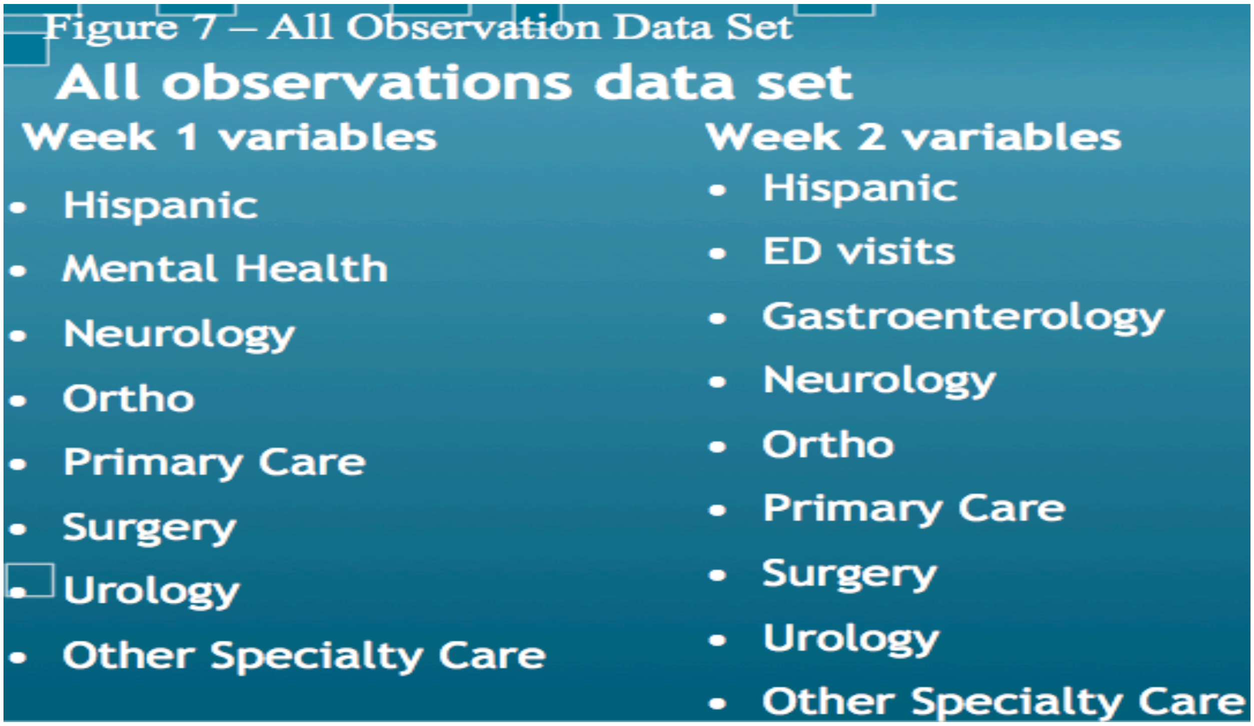


Figure 7 – All Observation Data Set

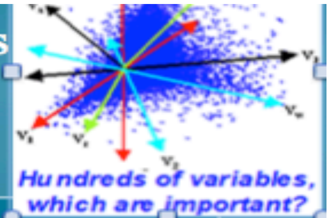
The forty models were composed of variations between 3 and 10 variables; and then 5 different variations were developed for each set of variable numbers; and the corresponding r-squared for each version. The five models consisting of 10 variables demonstrated r-squared values between 0.638 and 0.632. The five models consisting of nine variables yielded r-squared values of 0.627 and 0.618. The five models consisting of eight variables resulted in 0.613 and 0.599 r-squared. Models with seven variables ranged from 0.589 to 0.576 r-squared values. Six variable models were able to account for variation between 0.564 and 0.556 r-squared values. Models with five variables demonstrated r-squared values between 0.544 and 0.508. Models with four variables had r-squared values of 0.465 and 0.440, and finally, models with three variables demonstrated r-squared values between 0.413 and 0.351. Of particular interest with that two of the three variables were the impact drivers. The two most impactful variables were neurology in week 1 and ED visit in week 2, with the third variable being an adjustor.

Table 2 shows the r-squared range distribution of the All Observation Data Set for the 40 models developed by the number of variables in each set ranging from ten to three variables.

Table 2 – R-squared Distribution by Models

40 Models

- 5 models for 10 -3 variables sets



5 Predictor Models for Each Variable Set	R-squared range	Percentage
10	0.638 - 0.632	64 - 63%
9	0.627 - 0.618	63 - 62%
8	0.613 - 0.599	61 - 60%
7	0.589 - 0.576	59 - 58%
6	0.564 - 0.556	56%
5	0.544 - 0.508	54 - 51%
4	0.465 - 0.440	47 - 44%
3	0.413 - 0.351	41 - 35%

General findings when all 40 models were studied included: Neurology in week 1 as a strong predictor and was present in all forty models, and in week 2 Neurology was a predictor in models with ten and nine variables, and two of the eight variable models. ED visit in week 2 was a predictor in 39 of 40 models. ED visit week 1 was not a contributor. Orthopedic in week 1 was a superior contributor in week 1, but did not count in week 2. Orthopedic week 1 was in 35 of the models as an adjustor and it is expected these visits reflect post-surgical follow up appointments. As a result they are not predictors of admission prospectively, but are likely a reflection of post admissions not captured in week 1 and 2. Gastroenterology in week 2 was the third most powerful variable, while not a factor in week 1. Primary care was not a good predictor in driving to fill beds. Surgery in week 1 was an adjuster that did not impact occupancy, again likely reflective of post-surgical follow up visits and post admission impact.

Urology week 1 impacted 16 models and Urology week 2 impacted 19 models. It is probable the impact of these two variables is underrepresented, as in 2017 this specialty experienced surgeon vacancies. These variables will be interesting to study impact with another year's data.

Table 3 illustrates the five models generated with 10 variables. This table includes the standard variables in all five sets, as well as the five variables that appeared in various but not all models, and the r-squared for each model.

Table 3 - Data Sets with 10 Variables

Model	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	R-Squared
1	Neuro Wk 1	Ortho [illegible]	PC Wk [illegible]	Surg [illegible]	Urol Wk 1	ED Wk 2	Neuro Wk 2	PC Wk 2	Urol Wk 2	O. Spec Wk2	
	0.280	[illegible]	[illegible]	[illegible]	0.105	0.234	0.143	-0.015	0.119	-0.068	0.638
2	Neuro Wk 1	[illegible]	[illegible]	[illegible]	ED Wk 2	GI Wk 2	[illegible]	[illegible]	Urol Wk 2	O. Spec Wk 2	
	0.257	[illegible]	[illegible]	[illegible]	0.212	0.038	[illegible]	[illegible]	0.093	-0.047	0.638
4	Neuro Wk 1	[illegible]	[illegible]	[illegible]	Urol Wk 1	ED Wk 2	[illegible]	[illegible]	Urol Wk 2	O. Spec Wk 2	
	0.307	[illegible]	[illegible]	[illegible]	0.110	0.191	[illegible]	[illegible]	0.081	-0.071	0.636
5	Neuro Wk 1	[illegible]	[illegible]	[illegible]	Surg Wk 1	Urol Wk 1	[illegible] 2	[illegible] Wk 2	Urol Wk 2	O. Spec Wk 2	
	0.301	[illegible]	[illegible]	[illegible]	-0.093	0.129	0.177	0.103	0.095	-0.70	0.632
7	Neuro Wk 1	Ortho Wk 1	Surg Wk 1	Urol Wk 1	Hisp Wk 2	ED Wk 2	Neuro Wk 2	PC Wk 2	Urol Wk 2	O. Spec Wk 2	
	0.238	-0.081	-0.164	0.088	0.033	0.190	0.121	-0.037	0.105	-0.080	0.632

Standard Variables:
Neuro Wk 1
Ortho Wk 1
Surg Wk 1
Urol Wk 1
ED Wk 2
Neuro Wk 2
Urol Wk 2
O. Spec Wk 2

Variation:
ED Wk 1
PC Wk 1
Hisp Wk 2
GI Wk 2
PC Wk 2

Table 4 depicts the presence of variables in each variable model set from 10 variables to three variables. The key is color coded by 100%, 80%, 60%, 40%, and 20% variable presence in each of the model sets, and blank reflects zero presence.

Table 4

Variable Presence by Model

←Models→

V10	V9	V8	V7	V6	V5	V4	V3
Neuro Wk 1	Neuro Wk 1	Neuro Wk 1	Neuro Wk 1	Neuro Wk 1	Neuro Wk 1	Neuro Wk 1	Neuro Wk 1
ED Wk 2	ED Wk 2	ED Wk 2	ED Wk 2	ED Wk 2	ED Wk 2	ED Wk 2	ED Wk 2
Ortho Wk 1	Ortho Wk 1	Ortho Wk 1	Ortho Wk 1	Ortho Wk 1	Ortho Wk 1	Ortho Wk 1	PC Wk 1
Urol Wk 1	Neuro Wk 2	Urol Wk 2	GI Wk 2	GI Wk 2	GI Wk 2	PC Wk 1	Hisp Wk 1
Surg Wk 1	Urol Wk 2	GI Wk 2	PC Wk 2	PC Wk 2	PC Wk 1	GI Wk 2	ED Wk 1
Urol Wk 1	O Spec Wk 2	Surg Wk 1	Urol Wk 2	Urol Wk 2	Urol Wk 1	GI Wk 1	Ortho Wk 1
O Spec Wk 2	PC Wk 1	Urol Wk 1	PC Wk 2	PC Wk 1	Hisp Wk 2	Urol Wk 1	O Spec Wk 1
PC Wk 1	Urol Wk 1	PC Wk 2	Surg Wk 2	Surg Wk 1	Ortho Wk 2		
PC Wk 2	Surg Wk 1	PC Wk 1	Urol Wk 2	Urol Wk 1	PC Wk 2		
GI Wk 2	GI Wk 2	Neuro Wk 2	MH Wk 1	MH Wk 1	O Spec Wk 2		
ED Wk 1	ED Wk 1	O Spec Wk 2	O Spec Wk 2	O Spec Wk 2			
Hisp Wk 1	O Spec Wk 1	GI Wk 1	**KEY:**				
	PC Wk 2		100%	80%	60%	40%	20%

Table 5 denotes the variable impact by percentage of variable presences within each of the five models for variable sets 10 through 3.

Table 5 - Variable Impact

Variables

Variable	V10	V9	V8	V7	V6	V5	V4	V3
Neurology Wk 1	100%	100%	100%	100%	100%	100%	100%	100%
ED Wk 2	100%	100%	100%	100%	100%	100%	100%	80%
Ortho Wk 1	100%	100%	100%	100%	100%	100%	80%	20%
GI Wk 2	40%	40%	100%	100%	100%	80%	40%	
Urol Wk 2	100%	100%	100%	60%	20%			
PC Wk 2	60%	20%	60%	80%	100%	10%		
PC Wk 1	80%	80%	40%	40%	20%	20%	40%	40%
Urol Wk 1	100%	80%	60%	40%		20%	20%	
Surg Wk 1	100%	40%	80%	40%	20%			
Neuro Wk 2	100%	100%	40%					
PC Wk 2	60%	20%	60%	60%	80%	100%	20%	

Table 6 shows variables with the least impact on variable sets 10 through 3.

Table 6 - Least Variable Impact

Variables

Variables	V10	V9	V8	V7	V6	V5	V4	V3
ED Wk 1	20%	20%						20%
GI Wk 1			20%				20%	
Ment Hlt Wk 1				20%	20%			
O. Spec Wk 1		20%						20%
Hisp Wk 2	20%					20%		
Hisp Wk 1								20%
Ortho Wk 2						20%		
Surg Wk 2					20%			

After careful review and practical consideration of each model the most logical model was selected, Model 27. This included five variables with r-squared value of 0.517. The five variables are: Neurology week 1, Orthopedic week 1, ED visits week 2, Gastroenterology week 2, and other Specialty care week 2. Table 7 provides the beta coefficients of Model 27.

Table 7 – Model 27

Model 27 - R-squared value 0.517

Neurology Wk 1	Ortho Wk 1	ED Visit Wk 2	GI Wk 2	Other Spec Care Wk 2	# predictors	R-squared
0.245	-0.90	0.140	0.057	-0.032	5	0.517

Limitations

As an exploratory study this is a launching point for further study to enhance the ability of big data to predict children's hospital occupancy based on ambulatory visits. As this study was conducted with the data of one hospital it remains unclear if the results are scalable or reflective of the relationship between other children's hospital and pediatric ambulatory practices patterns. This model does not reflect variation in practice patterns between specialties or physicians. Further, it does not reflect the impact of workforce variation in staffing models or the impact of staff or physician vacancies that may influence ambulatory volume and efficiency. It also did not address or study predictions on neonatal census.

Unique and interesting influences identified in the literature were not able to be identified or recognized in this study that could impact predictability, such as trends in diseases including emerging disease prevalence or new treatments, seasonal influences, and casual influences that impact change in demand, change in physician availability or marketing mix (DeLurgio et al., 2009). Further, the literature recognized the cyclical or irregular influences that epidemics or natural disasters represent as uncontrollable influences on admissions (DeLurgio et al., 2009, Proudlove, Black & Fletcher, 2007). These considerations were not studied in this initial predictive model.

Chapter 4 - Findings

The first finding of the data was that the frequency of contact, not the number of children, was a more powerful predictor. All the billing data provided a better explanation than an individual child per day approach by 10%. It is likely that increased frequency captured activity reflective of patient intensity and acuity.

The second major finding was the illumination that there are major ambulatory predictors for in-patient occupancy. The major predictor was Neurology week 1, and Neurology week 2 was a predictor in 33% of the models. The second major predictor was ED visits week 2 which was present in all but one model, though ED visits week 1 was not a predictor. The third major predictor was Gastroenterology week 2.

Chapter 5 - Conclusion

As the country continues to demand the healthcare industry more effectively reduce costs, the ability for Children's Hospitals to predict in-patient admissions becomes increasingly important. Such a management tool currently does not existed. This exploratory study reached the aim of studying if big data from one children's hospital within a children's health system could predict in-patient admissions based on ambulatory visit data. It was determined this data can predict in-patient drivers of in-patient occupancy for greater than 50% of the variance. The variables that drive occupancy were a surprise and provide valuable insight into the next iterations of such predictive model development.

This initial model provides valuable insights for consideration in the development of the next model iteration. The next study should analyze Orthopedic and Surgery variables at week 3 and week 4 to assess the pre-surgical impact of admissions for non-emergency surgeries that are scheduled and require lengthy insurance authorization processes. These authorization processes can often take greater than two weeks before the surgery can be performed. Weeks 3 and 4 also allow time for families to coordinate their schedules to accommodate an elective surgery timeframe. Another consideration for this data set would be to re-analyze Urology week 1 and week 2 with another year of data to determine the impact of surgeon vacancy on in-patient occupancy predictions. Once the impact of Orthopedics week 3 and 4, Surgery week 3 and 4, and Urology week 1 and 2 (and possibly week 3 and 4) are examined the models will most likely better reflect the impact of surgical services on hospital occupancy.

The next step would then be to test the best models on another hospital data set to determine if the model is applicable in a different environment. Usage of the PEDSnet data uniquely has the ability to study variation linked to location and/or providers with the pediatric populations that are highly location specific. Goodman (2009) sites this as a historic pediatric limitation to date.

Summary

The pressure for the healthcare industry to move to improve quality and outcomes, while concurrently reducing costs is ever increasing and will continue until significant improvement is achieved. Self-governing children's hospitals have the ability to implement theorist Clay Christianson's (2013) theory that specialty hospitals can leverage economy-of-scale and offer focused expertise. This is the role children's hospitals play for the nation with only one children's hospital to 20 hospitals in the country (CHA, n.d.).

The lack of predictive modeling tools available to understand the impact of ambulatory practices on in-patient census was the drive behind this study. Such tools could greatly enhance both strategic and operational decisions that impact overall costs and improve decision-making. This exploratory study aimed to develop a predictive model for pediatric inpatient days based on ambulatory outpatient visits, including telehealth, urgent care, primary care, specialty clinics, and emergency department visits. The inherent relationship between ambulatory visits and inpatient days was the focus of this study that aimed to determine if in-patient days can be predicted based on sub-specialty practice.

Big data from PEDSnet was used to study this relationship from one children's hospital within a self-governing fully integrated children's health system, during calendar year 2017. The study determined this data can predict in-patient drivers of in-patient occupancy for greater than 50% of the variance. It was further determined that all billing data was more effective in predicting in-patient admissions than single child analysis by 10%.

Further study is needed to mature this model, however, the concept holds promise for more enlightened management decisions. The ability to enhance such a model could refine budgeting processes, capital planning, and master facility planning. Additionally, such information could more effectively guide workforce planning, staffing decisions, and patient throughput processes design in both the ambulatory and in-patient environments.

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Appendices

Appendix A

TRAUMA SERVICES

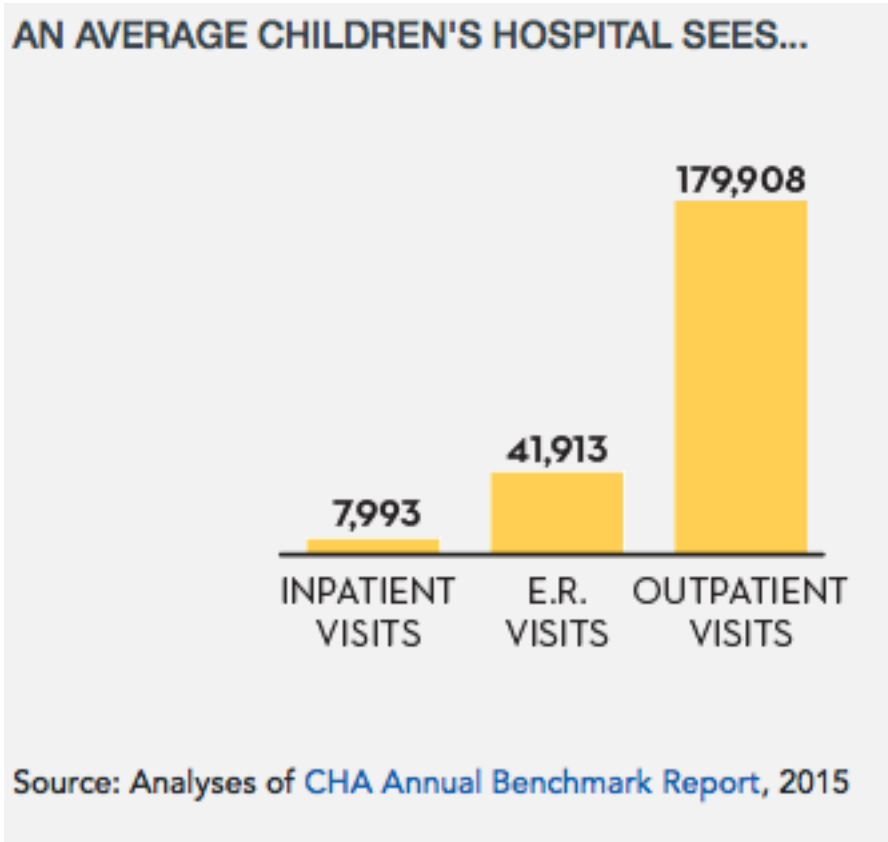
83% OF ACUTE CARE CHILDREN'S HOSPITALS ARE TRAUMA CENTERS

25% OF ACUTE CARE CHILDREN'S HOSPITALS ARE LEVEL I PEDIATRIC TRAUMA CENTERS

14% OF ADMISSIONS TO CHILDREN'S HOSPITALS ARE TRANSFERS FROM OTHER ACUTE CARE HOSPITALS

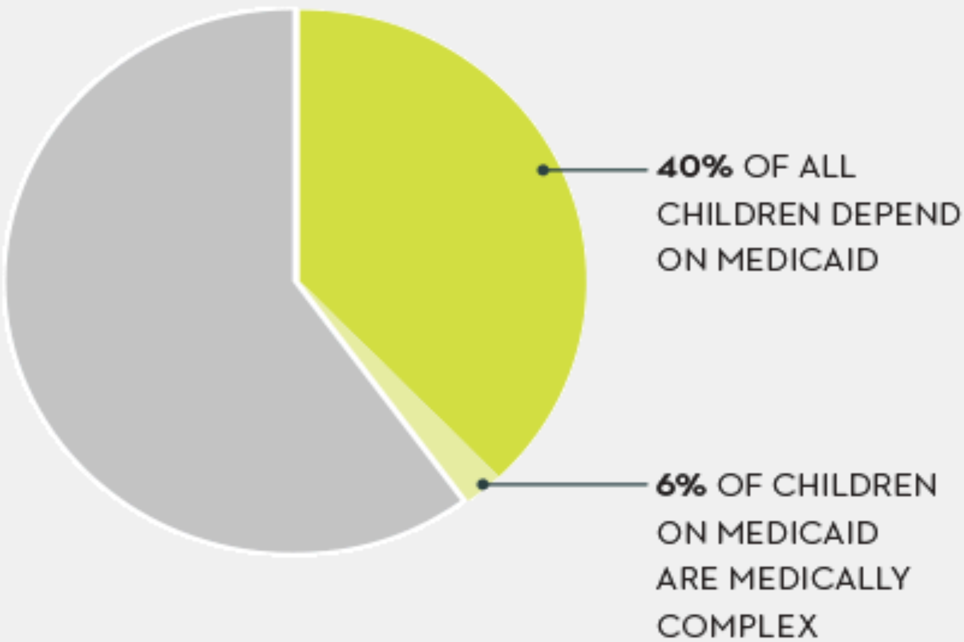
Sources: Analyses of CHA Annual Benchmark Report, 2015, only acute care hospitals included; Analyses from CHA, Pediatric Health Information System (PHIS database), 2014-2016

Appendix B


AN AVERAGE CHILDREN'S HOSPITAL SEES...
179,908
41,913
7,993
INPATIENT VISITS
E.R. VISITS
OUTPATIENT VISITS
Source: Analyses of CHA Annual Benchmark Report, 2015

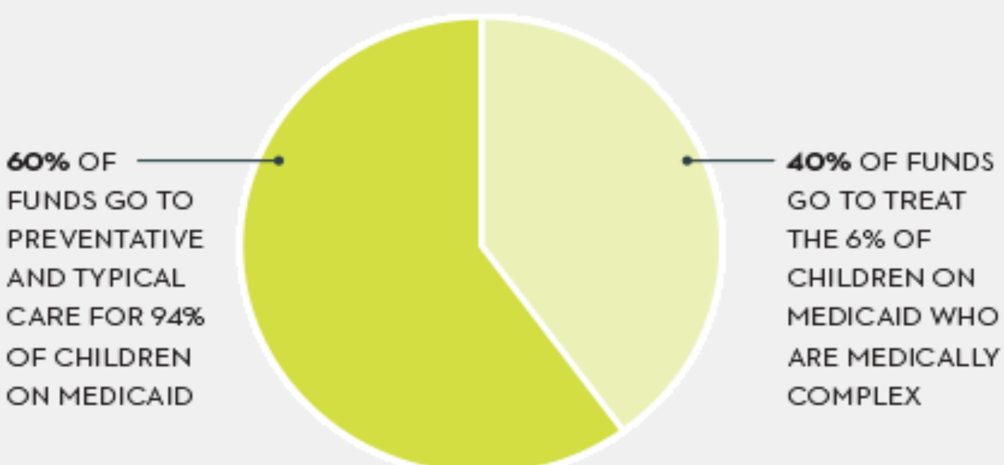
Appendix C

CHILDREN UTILIZING HEALTH CARE



Source: CHA Annual Survey on Utilization and Financial Indicators of Children's Hospitals, FY 2012

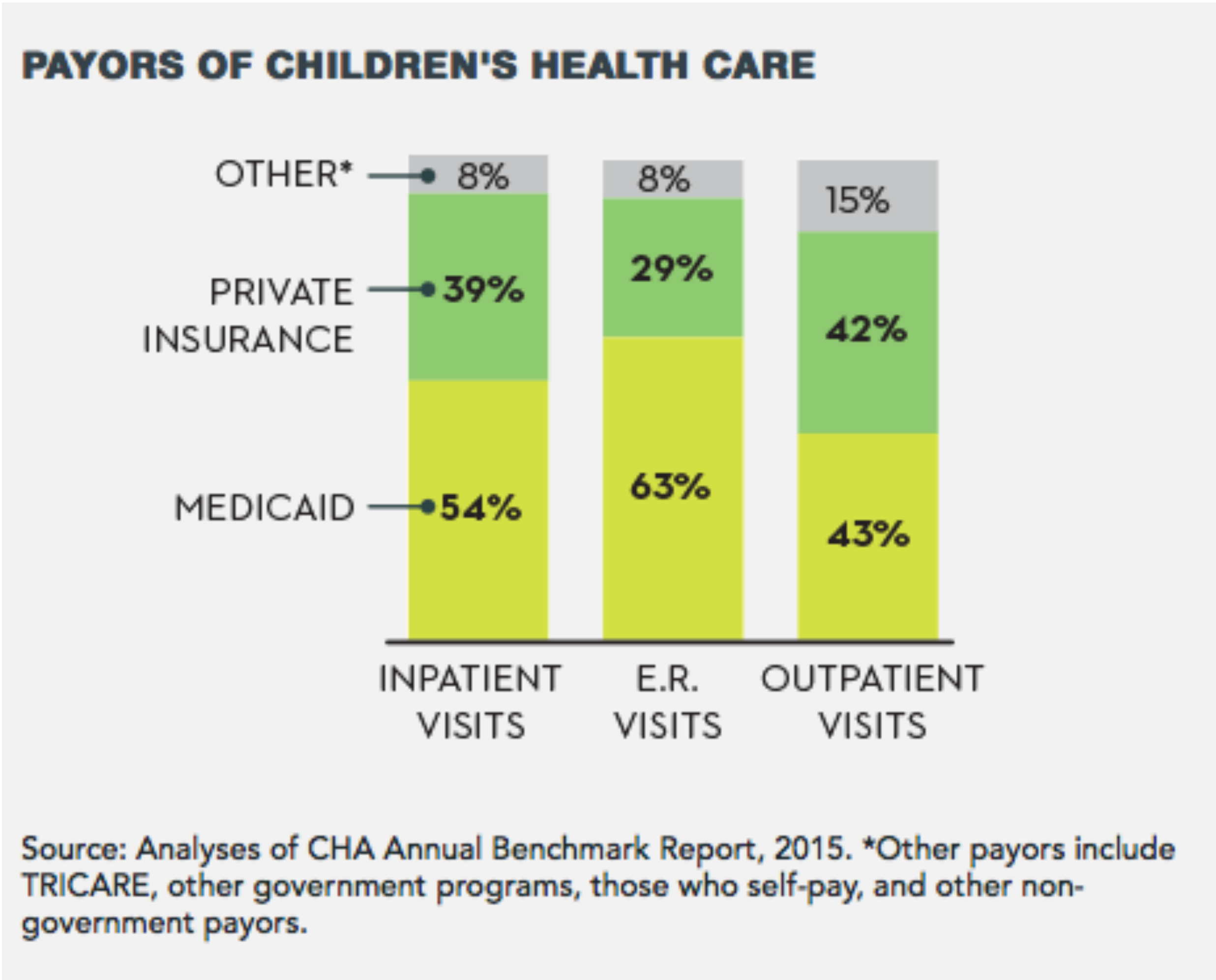
DISTRIBUTION OF MEDICAID FUNDING FOR CHILDREN



Source: Truven Healthcare Analytics analysis of 2009 to 2011 Truven Marketscan Multi-state Medicaid dataset, commissioned by CHA

Source: CHA, n.d.

Appendix D

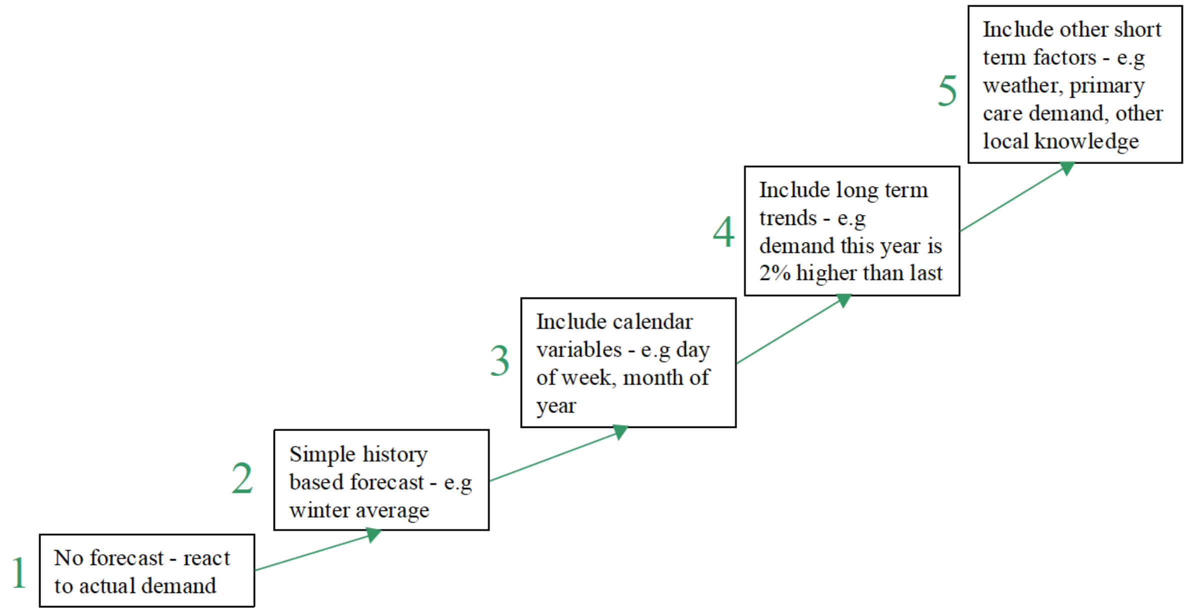


Source: CHA, n.d.

Appendix E

Levels of Sophistication in Planning Hospital Emergency Demand Forecast

Proudlove NC, Black S and Fletcher A (2007). "OR and the challenge to improve the NHS: modelling for insight and improvement in in-patient flows". *Journal of the Operational Research Society* 58:2, 145-158. OR and the challenge to improve the NHS http://dx.doi.org/10.1057/palgrave.jors.2602252



Source: Proudlove, Black, & Fletcher, 2007

Appendix F

Variable table

Data Source – Nemours Children's Health System PEDSNet

Data Timeframe - January 2017 – December 2017

Variable Name	Variable Type	Definition	Source	Calculation
PATIENT DEMOGRAPHICS				
Personid	Categorical	De-identified person number	PEDSnet	
Gest-age	Continuous	De-identified person's gestational age	PEDSnet	Median age/month/clinic
Ethnic	Categorical	Ethnicity source value – patients with Hispanic indicator	PEDSnet	Count/month/clinic
Black	Categorical	Percent of pt in clinic black	PEDSnet	Percent/month/clinic
White	Categorical	Percent of pt in clinic white	PEDSnet	Percent/month/clinic
Hispanic	Categorical	Percent of pt in clinic Hispanic	PEDSnet	Percent/month/clinic
Other	Categorical	Percent of other races in clinic	PEDSnet	Percent/month/clinic
Male	Categorical	Male = 1 Female = 0	PEDSnet	Percent/month/clinic
Age0-11	Continuous	0-1 years	PEDSnet	Median age/month/clinic
Age1-7	Continuous	1 – 7 years	PEDSnet	Median age/month/clinic
Age8-13	Continuous	8 – 13 years	PEDSnet	Median age/month/clinic
Age14plus	Continuous	14 years plus	PEDSnet	Median age/month/clinic
Medicaid	Categorical	Payor source	PEDSnet	Percent/month/clinic
Pvtpay	Categorical	Payor source	PEDSnet	Percent/month/clinic
Other	Categorical	Payor source	PEDSnet	Percent/month/clinic
PROVIDER DEMOGRAPHICS				
Prvidrid	Categorical	Provider volume	PEDSnet	# visits per provider id/month/clinic
Specialt	Categorical	Specialty volume	PEDSnet	# each specialty/month/clinic
SITE DEMOGRAPHICS				
Siteid#	Categorical	Id # for care site	PEDSnet	
Telehlth	Categorical	Location of care	PEDSnet	Percent/month/clinic
UC	Categorical	Location of care	PEDSnet	Percent/month/clinic

PC	Categorical	Location of care	PEDSnet	Percent/month/clinic
SpecCare	Categorical	Location of care	PEDSnet	Percent/month/clinic
ED	Categorical	Location of care	PEDSnet	Percent/month/clinic
Tot#vits	Continuous	Total ambulatory visits		Per month/clinic
DEPENDENT VARIABLE				
Aver Daily Census by week	Continuous	Daily census by unit totally to hospital census	Nemours Finance Report - NCH	In-patient days/week